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Real options, multi-objective optimization and the development of dynamically robust adaptive pathways

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ABSTRACT

In cases, which are characterized by deep uncertainty it is appropriate to develop dynamic and adaptable plans. This paper presents an approach that uses multi-objective genetic algorithms to automate the development of dynamic adaptation pathways for stormwater management for a tropical urban catchment located in Singapore. Pathways spanning a range of climate and landuse scenarios are developed. Three objectives, namely the economic value of flexibility or the real options value, the traditional net present value and flood robustness are balanced to develop the pareto optimal pathways. Given that the pathways are developed under a blanket of uncertainty it is certain that results will have to be re-computed at different time steps in the future. The assessment performed in this manner offers the ability to recompute results easily when adaptation becomes necessary. Comparison of the results obtained for the different landuse scenarios show that if done right, landuse planning can serve as a solution rather than a problem to cater to a changing climate. This notion coupled with the individual adaptation pathways enables the development of an adaptation strategy that helps outline short and long-term policies necessary to cater to an uncertain future.

1. Introduction

Any long-term environmental policy analysis must confront the fundamental challenge that the long-term future remains fundamentally unpredictable. While long-term forecasts generated by statistical extrapolations, causal models, or future narratives do provide valuable insights, savvy policy-makers cannot confidently rely on a projection of events decades into the future to inform their decisions (Lempert et al., 2009). Adaptive approaches enable decision makers to overcome the limit of predictability of the future. This ideology draws motivation from the need to develop plans that are not restricted to the outlined futures but instead can be adapted to cater to the future as it unfolds. A Central notion of this paradigm is the idea of replacing the traditional static optimal plan with a dynamically robust plan. A static optimal plan aims to reduce vulnerability under the largest range of plausible conditions (Walker et al., 2013) while a dynamically robust plan aims to be successful in a wide variety of plausible futures, through the ability to adapt the plan dynamically in response to how the future unfolds (Kwakkel et al., 2014). Given the irreversibility of built infrastructure and their long lifespans, planning infrastructure investments by means of dynamic robustness is more beneficial than doing so by that of static optimality. The notion of developing dynamically robust plans has been increasingly gaining traction over the past few years. This ideology has been followed in a handful of case studies across disciplines. Dynamically robust plans have been developed for coastal adaptation (Rosenzweig et al., 2011), climate risk adaptation (Lawrence and Manning, 2012; Ranger et al., 2010; Wilby and Dessai, 2010; Dessai and van der Sluijs, 2007; Willows et al., 2003) infrastructure planning (Ranger et al., 2013), river basin management (Groves et al., 2013; Jeuken and Reeder, 2011; Middelkoop et al., 2012), flood management (Haasnoot et al., 2013) and water supply resiliency (Beh et al., 2015; Groves et al., 2008).

Among the multiple adaptive approaches presented in literature, this study employs and further extends the adaptation tipping point and the adaptation pathway approaches. These approaches were chosen due to their ability to develop dynamically adaptable plans and their gaining popularity in the field of water resources development. Further, the adaptation pathways approach is not only robust to climate change but to all other sources of risk and uncertainty, including broader scenario uncertainties (e.g. socioeconomic) and uncertainties resulting from a lack of data (Ranger et al., 2013).

The Adaptation Pathway approach (Haasnoot et al., 2013) was specifically developed to support policymakers in making decisions in view of climate change adaptation. This approach entails developing an adaptable plan that can be modified in response to how the future unfolds. Individual adaptation actions are first identified and their

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Table 1
Portfolio of Adaptation Actions.

Configuration	Notation	Description
Current Drainage Configuration	A	The current configuration is maintained
Drainage Increase C1	B	15% increase from baseline drainage capacity
Drainage Increase C2	C	20% increase from baseline drainage capacity
Drainage Increase C3	D	30% increase from baseline drainage capacity
Drainage Increase C4	E	50% increase from baseline drainage capacity
Porous Pavements C1	F	50% of all available pavements covered
Porous Pavements C2	G	60% of all available pavements covered
Porous Pavements C3	H	80% of all available pavements covered
Green Roofs C1	I	20% of all available roof space covered
Green Roofs C2	J	35% of all available roof space covered
Green Roofs C3	K	50% of all available roof space covered
Combination 1	L	Green Roofs C1 and Porous Pavements C1
Combination 2	M	Green Roofs C2 and Porous Pavements C1
Combination 3	N	Green Roofs C3 and Porous Pavements C1
Combination 4	O	Green Roofs C1 and Porous Pavements C2
Combination 5	P	Green Roofs C2 and Porous Pavements C2
Combination 6	Q	Green Roofs C3 and Porous Pavements C2
Combination 7	R	Green Roofs C1 and Porous Pavements C3
Combination 8	S	Green Roofs C2 and Porous Pavements C3
Combination 9	T	Green Roofs C3 and Porous Pavements C3

respective adaptation tipping points are calculated under multiple outlined climate scenarios. Adaptation Tipping Points are the physical boundary conditions where acceptable technical, environmental, societal or economic standards may be compromised (Haasnoot et al., 2011). Once an Adaptation Tipping Point is encountered, the system cannot continue to perform as expected and requires the implementation of another adaptation action. Simulation models are used to establish tipping points for predefined adaptation actions, under various scenarios. This enables the sequencing of adaptation actions to form adaptation pathways. The adaptation pathways are then combined to develop an adaptation pathways map.

Building dynamically robust plans by means of an adaptive pathway approach thus entail the consideration of multiple plausible futures, a large number of adaptation actions that can be implemented in response to these futures and the multiple ways these actions can be applied in isolation and combination to meet objectives all along the planning horizon. In addition to this, there are also socio-economic factors and different planning perspectives of decision makers that can impact the outlining and selection of these plans. Only when we understand the interplay of factors can we outline a map that can cater to any reality i.e. that is truly dynamically robust. Analysing a problem in this manner results in the 'curse of dimensionality' and is severely limited in practice by the necessary computational burden (Webster et al., 2012; Heer and Maussner, 2018). Once built, the adaptation pathways map provides an overview of sequences of possible actions that can be implemented under an uncertain climate. While having the entire solution space available has its own benefits in terms of visualizing all possible available solutions, it still leaves decision makers in an impossible position to choose among the multiple available pathways. This creates a need for further assessment of the developed adaptation map to trim down the large number of developed solutions into a more manageable subset. In addition, as every plan must be reassessed at specific intervals, the assessment must be repeated periodically. As the adaptation pathway map is currently drawn manually (Manocha and Babovic, 2017; Haasnoot et al., 2013) it makes the future re-assessment of the plan equally computationally intensive.

This paper aims to address two main objectives. The first objective is to show how the dynamic adaptive pathways approach developed for flood management in the Kent Ridge Catchment (Manocha and Babovic, 2017) can be supported computationally. The second objective is to extend the adaptive pathway approach by automating the identification of a sub-set of dynamically robust pathways that meet multiple objectives offering a trade-off between maximizing the flexibility of adapting to changing climate scenarios, maximizing robustness to a range of climate scenarios while being also cost effective. This is done by means of multi-objective evolutionary algorithms.

The rest of the paper is organized as follows: Section 2 offers in an introduction to the Kent Ridge case study. The application of the approach and the manner in which the optimization problem has been formulated is described in the Methodology section (Section 3). Results and discussions are presented in Section 4, followed by a conclusion in Section 5.

2. Introduction to the case study

The approach presented in this paper is illustrated by means of the Kent Ridge Case Study. The Kent Ridge Catchment is 85,000 square meters in size and is located in the south of Singapore, within the campus of the National University of Singapore. This catchment contains all the main land use types of Singapore and hence can be considered as reasonably representative from a hydrological point of view.

Singapore's Second National Climate Change Study determines that annual rainfall totals show a statistically significant upward trend over the last 30 years (CCRS, 2015). Singapore has become hotter and more prone to heavier storms (PUB, 2016). Thus there is a need to introduce measures to significantly reduce and manage the flood risks that may be increased due to a changing climate. In accordance with this notion, the adaptation tipping point and the adaptation pathway approach was employed in a previous study (Manocha and Babovic, 2017) to develop adaptive plans for flood management in the Kent Ridge Catchment. This paper employs this case study as a starting point. The adaptation actions and assessment scenarios employed in the study are presented here for brevity. For details, please refer to the original study.

The portfolio of adaptation actions considered in this study includes both traditional grey and innovative green infrastructure solutions, namely: expansion of drainage canals, implementation of green roofs and the implementation of porous pavements. These, in varied configurations, make up the set of adaptive actions assessed in this study. They are summarized in Table 1. The notations specified, are used to address the actions in the subsequent sections of the paper. The configurations of adaptive actions are selected in alignment with the broad national objectives (Manocha and Babovic, 2017).

Scenarios developed for this study cover a range of possible climatic and land-use futures. This is done to study the individual and coupled impact of climatic and anthropogenic influences on the timing of reaching an adaptation tipping point. The climate scenarios were

Table 2
Climate Scenarios.

Baseline	Extrapolation of historical trend
W1 (Wet 1)	10% wetter climate (2016–2100), compared to baseline
W2 (Wet 2)	25% wetter climate (2016–2100), compared to baseline
D1 (Dry 1)	10% dryer climate (2016–2100), compared to baseline

Table 3
Land-use Scenarios.

Land use type	% of land use in Current Scenario	% of land use in Green Scenario	% of land use in Sustainable Grey Scenario
Impervious	10	5	15
Grass on a steep slope	10	10	10
Grass on a mild slope	18	13	18
Mixed grass and trees	15	15	10
Natural Vegetation	30	40	12
Roofs	17	17	35

developed using the IPCC RCP's (Representative Concentration Pathways) as a guiding basis (Pachauri et al., 2014). Under the 4.5 and 8.5 scenarios, a 10.3% and a 26.8% change in rainfall is expected on the positive side (CCRS, 2015). The climate scenarios used in this case study are presented in Table 2. The land use scenarios include a Baseline (Landuse B), Green (Landuse G) and Sustainable Grey (Landuse SG) land-use scenario. The baseline scenario is reflective of the existing land use practices. The green scenario follows a sustainable outlook. The sustainable grey landuse allows for construction of buildings on account of green spaces but mandates retrofitting the developments in a predefined proportion with stormwater management solutions such as green roofs and/or porous pavements. The land use scenarios are presented in Table 3.

3. Proposed methodology

This paper aims to extend the adaptive pathway approach to enable the sub-selection of a preferred set of pathways in a computationally effective manner. The overall approach employed is outlined in Fig. 1.

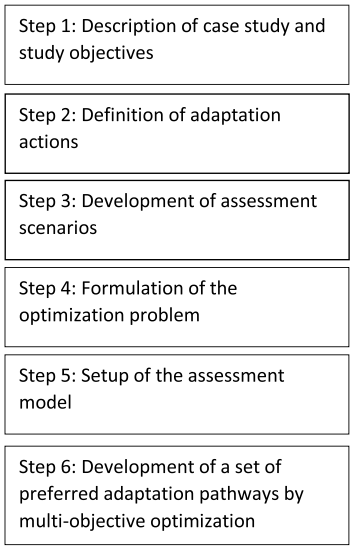
Step 1: Description of case study and study objectives
Step 2: Definition of adaptation actions
Step 3: Development of assessment scenarios
Step 4: Formulation of the optimization problem
Step 5: Setup of the assessment model
Step 6: Development of a set of preferred adaptation pathways by multi-objective optimization

Fig. 1. Methodology.

Steps 1 through Step 3 have been discussed in Section 2. The use of scenario analysis is considered most appropriate for determining the portfolio of diverse solutions, as it enables alternative plausible future dynamic pathways to be developed (Beh et al., 2015). The purpose of outlining different scenarios is not to predict the future, but to enable the exploration of a relatively small number of different plausible futures that are generally not equally likely (Mahmoud et al., 2009). For this reason, scenario analysis has been adopted widely as a means of assessing the impact of deep uncertainty in water resources planning (Kasprzyk et al., 2013, 2012). The scenarios outlined in this study consists of climatic and anthropogenic (land use) scenarios. These are discussed in Section 2. It is important to iterate that, given the nature of the adaptive approach, we can easily reassess the pathways in the face of new climate scenarios if necessary at a later time in the future.

When identifying a set of optimal solutions under deep uncertainty, it is critical to identify a portfolio of potential solutions that are able to respond to different future conditions (Korteling et al., 2013). It is thus proposed to use a multi-objective optimization approach to identify the set of preferred pathways (solutions) that are able to cater to deep uncertainty. The pathways are developed independently for each land use scenario for the entire planning horizon. The outlined climate scenarios serve to provide different plausible climate futures that the identified pathways should be optimized for.

Optimization is widely accepted as a tool to support decision making. Traditional decision-making usually relies on the outcome of a cost-benefit analysis in the context of single objective optimization, which often fails to consider multiple environmental and social objectives simultaneously (Chang et al., 2012). Evolutionary Algorithms have proved to be flexible and powerful in solving complex water resources problems (Nicklow et al., 2009) and are able to identify the best set of alternatives that represent multi-objective trade-offs i.e. identify the set of non-dominated solutions. A solution is said to be non-dominated if the performance of this solution is not exceeded on all objectives by any other solution (Reed et al., 2013). These set of non-dominated solutions makes the various trade-offs or conflicts among the different objectives explicit, offering a form of posterior decision support (Coello et al., 2007). Currently, a wide variety of alternative multi-objective evolutionary algorithms are available for solving multi-objective optimization problems. In this paper, we use the Non-dominated Sorting Genetic Algorithm-II (NSGA-II) (Deb et al., 2002). This is a well-known algorithm that has been applied in a wide range of optimization problems.

The optimization problem that we are trying to solve in this study includes three objective functions. The first is the maximization of the value of flexibility that a given pathway offers. Flexibility can be understood as the ability of a system to adapt in the face of a changing future. Although flexibility has been used in optimization studies (Beh et al., 2015) it has been used in the context of quantitively assessing the percentage of futures or scenarios that a given configuration can be adapted to in a cost-effective manner. This study presents for the first time the use of flexibility in terms of its economic value (measured in Singapore dollars) as an objective function of the multi-objective optimizer to aid in the sub-selection of a preferred set of adaptation pathways. The economic value of flexibility of a given pathway under uncertainty is calculated by means of a Real Options Analysis. The steps undertaken to perform this assessment is out of the scope of this paper. The methodology used is similar to that presented in a previous study (Manocha and Babovic, 2016). This metric is able to capture the economic gain resulting from the managerial flexibility and the ability to defer an action or investment under an uncertain environment.

The second objective is the maximization of the Net Present Value (NPV) of the given pathway. This is akin to finding a pathway that is cost effective. The third objective of flood robustness aims to minimize the cost of flood damage i.e. maximize the flood robustness. The values of the objective functions for the pathways to be optimized are calculated with the aid of the assessment model for each climate scenario.

Table 4
Pareto front and objective function values for the Baseline landuse.

Pathway Number	Phase 1	Phase 2	Phase 3	Phase 4	VOF (SGD)	NPV (SGD)	Flood Damage (SGD)
1	A	B	D		188,003	11,883	4,892
2	A	B	D	F	156,377	−32,283	554
3	A	C	D	F	154,389	−26,903	554
4	A	C	E		150,723	−16,361	554
5	A	D			150,119	−6,452	2,480
6	A	D	E		137,425	1,756	0
7	A	D	F		129,670	9,214	0
8	A	E			105,328	12,534	0

Details of the assessment model are available in (Manocha and Babovic, 2017). The mean value of objective functions across the outlined climate scenarios is used for finding the optimized pathways.

We implemented the algorithm in Matlab 2015R using the gaoptimset library for genetic algorithms. We ran the optimization for 1000 generations and a population size of 100. To assess the robustness of results to randomization we ran the optimizer three times. Identical Pareto front of sets of pathways was obtained each time. These pathways on the Pareto front constitute the preferred set of pathways for each outlined landuse.

4. Results and discussions

When dealing with multiple, competing objectives, there is generally no single optimal solution, but a collection of solutions that are all optimal. This is because, for these solutions, improvements in one objective can only be achieved at the expense of degradation in at least one of the other objectives. The Pareto fronts comprising of the pathways optimized for the objective functions are presented in Tables 4–6.

We use path values plots in order to better understand the trade-off between the objective functions. The path value plots are presented in Figs. 2–4 for the baseline, green and sustainable grey landuse respectively. Ideally, we would like to maximize the value of flexibility and the NPV while simultaneously having minimal flood damage.

The value of flexibility is essentially the pathways valued as real call options. On the other hand, the NPV is a standard capital budgeting exercise that justifies the costs of a given pathway against its expected benefits under a condition of no flexibility. While the Real Options valuation considers the balance of costs and benefits in valuing the flexibility it is important to also understand the actual expenses that have to be borne if a pathway is implemented. This is the rationale in using the value of flexibility and the NPV as objectives in the optimization. The higher the value of each of these criterions the better the pathway is. The figures indicate that a higher flexibility is accompanied by a low NPV i.e. the maximization of one criterion can only be achieved at the compromise of the other. This is expected as imparting flexibility to investments carries an associated cost. The flood damage does not show a strong correlation with either of the other objective functions. The level of acceptable flood damage or conversely the level of flood robustness required has to be decided by the decision makers based on the level of protection that has to be afforded to the area in question. For example, while areas that house critical infrastructure such as hospitals, defense installations etc., or are heavily populated may require a higher level of flood robustness than areas that are majorly open spaces such as parking lots, open green areas, playgrounds etc. They can be protected with simpler cost-effective flood management measures.

It is interesting to note that the pathways that emerge as members of the Pareto front are dominated by adaptation actions that advocate the expansion of the existing drainage systems in varied configurations. This is consistent across all three landuse scenarios. The sustainable grey landuse scenario requires an increase in capacity of a configuration higher than that warranted by the baseline and the green landuse scenario due to the increased paved and roof areas contributing to a higher runoff under the same climate scenarios. The increase in draining capacity is supplemented with the implementation of porous pavements (action F: 50% of all available pavements covered) in the baseline and green landuse scenario. The Pareto front for the sustainable grey landuse scenario, however, comprises of pathways that use a combination of increased drainage capacity with either porous pavements (action G: 60% of all available pavements covered) or green roofs (action I: 20% of all available roof space covered). The CAPEX and maintenance cost of expanding the drainage capacity is considerably lesser than that of implementing alternative solutions such as green roofs and porous pavements (Manocha and Babovic, 2017). This is a contributing factor for solutions favoring draining expansions dominating the Pareto front and being among the preferred set of pathways. With improvements in technology and associated decrease in cost of these alternative solutions, it is possible that the preferred set of pathways may include more of such adaptation actions.

The assessment has been carried out across three landuse scenarios to depict the possible national objectives that the government may adopt. Given the attention that landuse planning receives in Singapore and the fact that Singapore does not face challenges of urban sprawl, exponential population growth, illegal settlements etc. it is highly unlikely that the future land use will be uncertain. Thus, land use planning can serve to be a part of the solution rather than the problem. While the landuse scenarios, in reality, will not mirror the landuse scenarios used

Table 5
Pareto front and objective function values for the Green landuse.

Pathway Number	Phase 1	Phase 2	Phase 3	Phase 4	VOF (SGD)	NPV (SGD)	Flood Damage (SGD)
1	A	B	D		139,021	−9,213	2,341
2	A	B	D	E	134,595	−142,457	1,055
3	A	B	D	F	126,656	−49,236	550
4	A	B	E		122,726	−26,499	291
5	A	B	F	D	122,147	−19,865	1,229
6	A	C	E		118,699	−20,328	0
7	A	D			118,671	−18,641	0
8	A	D	E		117,857	−16,959	291
9	A	D	F		116,936	−16,037	0
10	A	F	D		113,830	−10,788	0

Table 6
Pareto front and objective function values for the Sustainable Grey landuse.

Pathway Number	Phase 1	Phase 2	Phase 3	Phase 4	VOF (SGD)	NPV (SGD)	Flood Damage (SGD)
1	A	D	E		316,248	127,827	8,392
2	A	D	E	I	239,136	88,090	2,225
3	A	D	G		233,774	−80,223	1,388
4	A	E			226,699	65,754	0
5	A	E	I		214,294	99,325	0

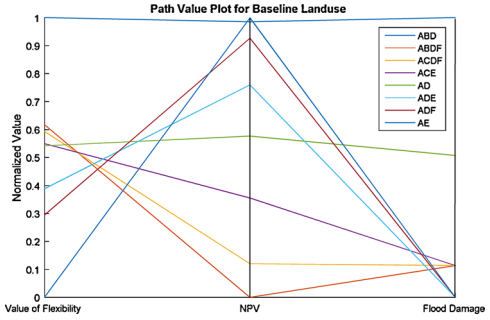

Fig. 2. Path Value Plot for Baseline Landuse.

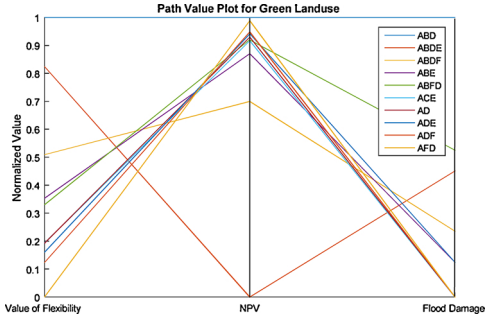

Fig. 3. Path Value Plot for Green Landuse.

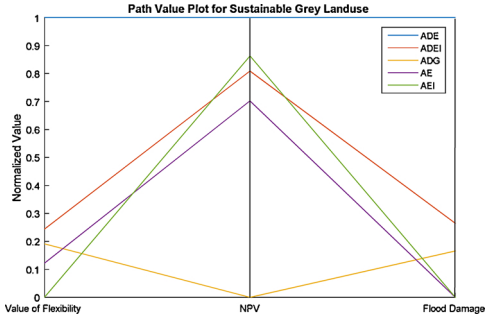

Fig. 4. Path Value Plot for Sustainable Grey Landuse.

in this study, the use of these scenarios still shed light on the implications that different national planning perspectives can have on stormwater management and help decide the adaptation actions to be implemented in each case respectively.

The previous work of discovering the adaptation pathways presented in (Manocha and Babovic, 2017) relied on using an assessment model to calculate the adaptation tipping points and subsequently manually outlining the individual pathways. That approach had two main drawbacks. Firstly it is a very time-consuming process to develop the entire solution space consisting of a multitude of pathways. Secondly, it led to the discovery of a very large number of solutions. Assuming a baseline climate, the results of the previous study show 90 possible pathways under the baseline, 152 possible pathways under the green and 245 pathways under the sustainable grey landuse. These pathways were then ranked based on their economic performance to develop the subset of preferred pathways. In contrast, using evolutionary algorithms to automate the search for the subset of preferred pathways eliminates the need for manually outlining the pathways. In addition to removing the potential mistakes due to human error, it also offers the ability to recompute results easily when the need to add in new adaptation actions or changing performance metrics of existing adaptation actions arises. Given that the pathways are developed under a blanket of uncertainty it is almost certain that the need to re-compute the results at different time steps in the future will arise. In addition to this, given a real-world scenario, it is highly unlikely that the selection of the subset of preferred pathways will be based on maximizing a single objective. Rather, the choice will be made based on optimizing multiple objectives.

The subset of preferred pathways resulting from using multi-objective genetic optimization for the three landuse scenarios are shown in Figs. 5–7. Porous Pavements are abbreviated to PP and green roofs are abbreviated to GR. The figures can be read like a map indicating several possible routes (adaptation pathways) to reach the desired point (the year 2100) in the future. Each adaptation action, (shown on the Y-axis) is depicted by a specific color (Refer to Table 3 for detailed configuration of the adaptation actions). The X-axis represents the adaptation tipping points and the corresponding years they are exercised under different climate scenarios. The squares represent interchange points, where one can switch to a different adaptation action. The color of the square indicates the action from which one has to switch. The black bars mean that a tipping point is reached and that the current configuration can no longer perform as expected, requiring a switch. In order to understand all the available options once a tipping point is reached, follow the vertical color bar of the existing action until it reaches the interchange squares. Each pathway is defined by the particular sequencing of actions that allows the configuration to meet desired objectives.

While having the entire solution space available has its own benefits in terms of visualizing all possible available solutions, it still leaves decision makers in an impossible position to choose among the multiple available pathways. By using a multi-objective genetic algorithm to develop adaptation pathways, the solution space is trimmed substantially. In developing the subset of preferred pathways, a few pathways are presented a part of the result as opposed to selecting a single best pathway from the Pareto front. The decision as to the exact actions and plans to be implemented is left to the decision makers. The subset of pathways thus acts to guide decision-makers in the development of a baseline plan that will be followed given the climate changes as expected and also sheds light on additional actions that can be implemented if the future differs largely from one that is expected. The baseline plan enables the understanding of the sequencing of actions. It aids in planning for implementation of adaptation action(s) that have to be carried out in short term (the first phase of development) and in preparing for those that have to be implemented in the long term (the subsequent phases of development). This understanding can be very beneficial to decision makers, as it helps in establishing an approximate timescale for adaptation. This is necessary as the implementation of measures on a large scale requires long-term planning.

Depending on the nature of the study, there can arise be a need to consider other objective functions such as environmental costs and

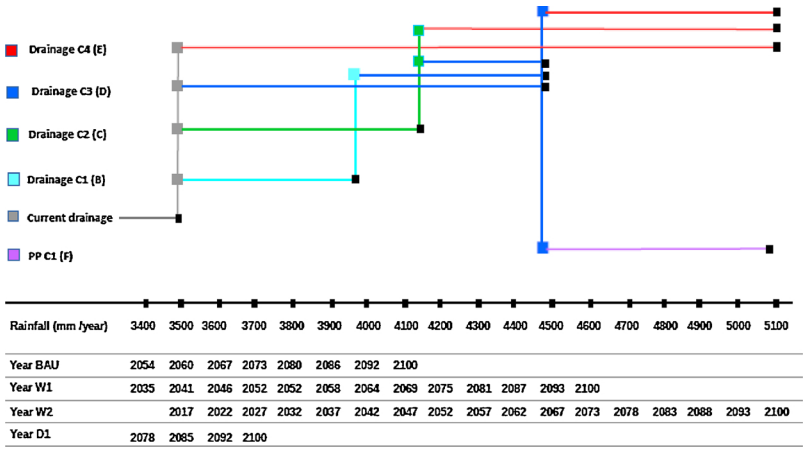

Fig. 5. Sub-set of preferred pathways derived by means of multi-objective genetic optimization for the baseline landuse.

benefits, land pricing, public preferences or indexes based on national objectives etc. The given framework can easily be extended to incorporate these objective functions into the existing or replace the given objective functions as deemed appropriate by decision makers. It should be expected that this may change the members of the Pareto front.

We have used NSGA-II as the algorithm that enables solving the multi-objective optimization problem. While the NSGA-II remains the most popular MOEA in active use today, it can perform poorly in certain classes of problems. Subsequent to the NSGA-II, a new generation of MOEAs have emerged that have had a large impact in water resources and beyond (Reed et al., 2013). It is to be noted that the approach presented in this paper is not constrained to using NSGA-II. The use of other modern algorithms can be explored if warranted by the complexity of the case study.

5. Summary and conclusions

Traditional water resources planning and analysis methods are based on requirements that are unrealistically deterministic (Medellín-Azuara et al., 2007). The tradition 'predict then build' approach used in designing policies carry the risk of implementing solutions that do not perform as expected in environments characterized by uncertainty. This can have large negative implications when used to design irreversible and cost-intensive infrastructure solutions. Thus given that we cannot predict the future with certainty, there is a need to use alternative approaches to design climate adaptation plans and policies. New approaches such robust decision-making aim to address this limitation of predictability by developing plans that are capable of catering to a wide ensemble of futures i.e. by developing static optimal plans. However, given the nature of climate change, it is more beneficial and appropriate to develop plans that can be adapted to how the future unfolds i.e. develop dynamically robust plans.

The adaptation pathway approach provides a framework to develop dynamically robust plans for climate adaptation. The adaptation pathway map developed by means of this approach provides decision makers with an overview of all actions available to deal with a changing climate and also provides guidance on the sequencing and required timing of adaptation. Given the array of adaptation actions and the various ways in which they can be combined to make adaptation pathways, the entire solution space can contain a very large number of solutions which can leave decision makers in a difficult position of selecting from amongst them. While it is beneficial to have an overview of all possible available solutions, all solutions may not be desirable when considered from different perspectives.

The framework of using multi-objective optimization together with the adaptation pathway approach is a way to automate the outlining and sub-selection of adaptation pathways. The automation allows for easy reassessment of plans at a later time step, under new scenarios, in light of newly available technologies (adaptation actions) or under changing perspectives of decision making. This is especially valuable when the developed framework is used to make decisions under deep uncertainty for complex case studies that involve multiple scenarios and multiple adaptation actions where the number of developed pathways could potentially be very large.

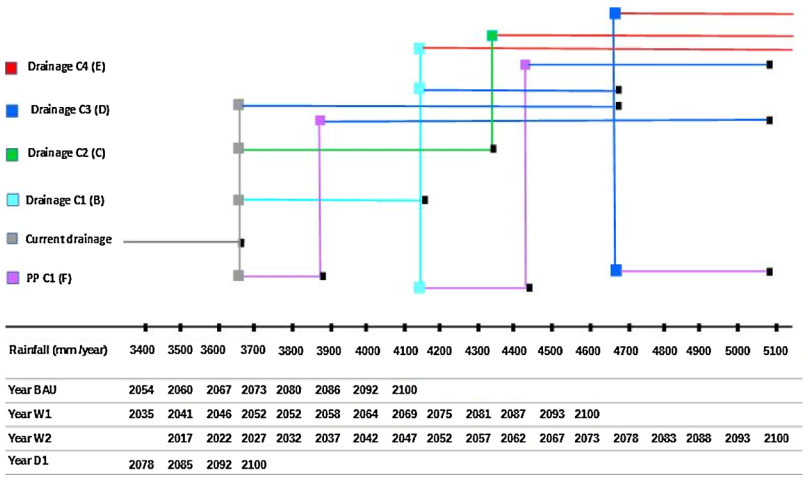

Fig. 6. Sub-set of preferred pathways derived by means of multi-objective genetic optimization for the green landuse.

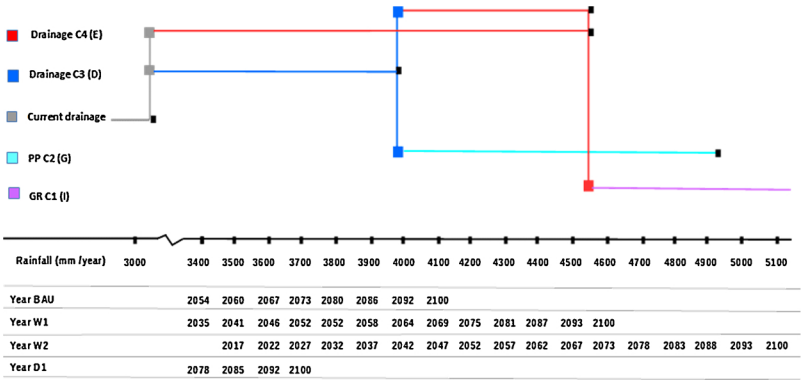

Fig. 7. Sub-set of preferred pathways derived by means of multi-objective genetic optimization for the sustainable grey landuse.

The notion of using evolutionary algorithms to sub-select adaptation pathways has been employed in the Waas case study (Kwakkel et al., 2014). They arrived at 11 unique pathways from the 74 identified non-dominated pathways by means of post-processing the non-dominated pathways based on sequencing rules appropriate for the study. In contrast, this study added the sequencing rules for the development of pathways for flood management for the Kent Ridge case study upfront as constraints within the genetic algorithm, thus requiring no post-processing of generated results. In addition, the objective functions used in the Waas case study are directly related to flooding while the objectives functions considered in this study are all economic in nature.

The ability of this framework to discover reliable pathways is heavily dependent on inputs from decision makers. This is because any given strategy dealing with the development of large-scale public infrastructure will only be successful if it aligns with the national objectives of the nation. It is thus recommended that when using this approach to develop pathways for large-scale projects, decision makers be involved from the conception stage.

To demonstrate the utility of the proposed framework, it is applied to a case study for designing adaptation pathways for stormwater management in a tropical urban catchment located in Singapore. The optimization objectives used in this study include the value of flexibility, the tradition net present value addressing and the flood damage associated with a given pathway. The selection of objective functions can be updated in line with the requirements and preferences of decision makers. The value of flexibility, calculated by means of real options adds novelty to the study as it provides a way to quantitatively assess the economic value added by the ability of a solution to adapt under uncertainty. It is appropriate in the context of designing dynamic robust plans.

The case study used in this paper involves making decisions for a small tropical urban catchment. It is recommended that this approach be applied to cases that involve a higher level of complexity. In addition, the current manner in which scenarios are described encompasses only a possible range of future scenarios. Although given the nature of the adaptive approach, we can easily reassess the pathways in the face of new climate scenarios, it will also be interesting to modify the assessment scenarios to see the response of the system when dealing with “unknown unknowns” or black swan events (Taleb, 2012). The performance of solutions in such events can be used as additional objective functions if deemed necessary by the decision makers. Finally, even though the approach of using multi-objective optimization to support the development of dynamic pathways has been demonstrated in the context of stormwater management, it can be applied to other domains that warrant decision making under uncertainty.

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